

Research - Distributed GPU Compute Sharing via libp2p for Low-Power Browser AI Inference

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Abstract

Local AI inference for browser tasks—including vision-language processing, speech recognition, and neural translation—requires significant computational resources that may exceed the capabilities of low-power devices such as smartphones, tablets, and older laptops. This paper presents the design of a distributed GPU compute sharing system for the Kathon cryptographic browser that enables peer-to-peer AI inference acceleration across trusted devices using libp2p networking. The system partitions neural network inference workloads across participating peers using tensor parallelism, with encrypted communication channels, verifiable computation proofs, and incentive mechanisms based on the .aioss cryptographic ledger. We address key technical challenges: heterogeneous device discovery with capability advertisement, dynamic workload partitioning for variable peer availability, encrypted inference that prevents input reconstruction, and fault tolerance through redundant computation. Simulated benchmarks across a 16-peer testbed demonstrate 3.8x speedup for Whisper transcription and 4.2x speedup for Qwen 2.5 VL inference on low-power client devices. A security analysis confirms that encrypted inference provides semantic security against honest-but-curious peers. The system enables Kathon to deliver AI features on devices that lack the local compute capacity for real-time inference.

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Local AI inference for browser tasks—including vision-language processing, speech recognition, and neural translation—requires significant computational resources that may exceed the capabilities of low-power devices such as smartphones, tablets, and older laptops. This paper presents the design of a distributed GPU compute sharing system for the Kathon cryptographic browser that enables peer-to-peer AI inference acceleration across trusted devices using libp2p networking. The system partitions neural network inference workloads across participating peers using tensor parallelism, with encrypted communication channels, verifiable computation proofs, and incentive mechanisms based on the .aioss cryptographic ledger. We address key technical challenges: heterogeneous device discovery with capability advertisement, dynamic workload partitioning for variable peer availability, encrypted inference that prevents input reconstruction, and fault tolerance through

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1. Introduction

Local AI inference has become a cornerstone of privacy-preserving browser features. Kathon’s AI capabilities—including natural language omnibox queries, visual page analysis, speech transcription, and bionic reading typography—all rely on neural network inference performed on-device. However, the computational demands of these models, even in quantized form, exceed the capabilities of many consumer devices [1].

A Qwen 2.5 VL 2B model in Q4 quantization requires approximately 2.4 GB of RAM and achieves 25-40 tokens/second on CPU or 80-120 tokens/second on a midrange GPU [2]. A Whisper small.en model requires 680 MB and achieves 15-25x real-time factor on CPU [3]. These performance levels are adequate on recent laptops but insufficient on devices with 4GB RAM or integrated GPUs.

Distributed GPU compute sharing offers a solution by pooling resources across trusted devices. Users with multiple devices (laptop, desktop, tablet, phone) can share compute resources for AI inference, with workloads dispatched to the most capable available devices. The Kathon Distributed GPU Compute (DGC) system uses libp2p for peer discovery, encrypted communication channels based on Noise protocol, and tensor parallelism for workload distribution.

2. Literature Review

2.1 Distributed Neural Network Inference

Distributed inference partitions neural network computation across multiple devices. Three primary paradigms exist: data parallelism (each device processes different input samples), model parallelism (different layers on different devices), and tensor parallelism (individual tensor operations partitioned across devices) [4].

Tensor parallelism, introduced by Shoeybi et al. (2019) for Megatron-LM, partitions matrix multiplication operations across devices by splitting weight matrices along rows or columns [5]. This approach is particularly suitable for transformer architectures [6]. PipeDream by Harlap et al. (2018) introduced pipeline parallelism for distributed training [7]. Petuum by Xing et al. (2015) provided a general framework for distributed machine learning [8].

2.2 Peer-to-Peer Networks for Compute

libp2p is a modular network stack for peer-to-peer applications, providing transport-agnostic peer discovery, NAT traversal, and encrypted communication [9]. IPFS and Filecoin use libp2p for decentralized storage [10]. Research by Guerraoui et al. (2021) examined incentives for computational resource sharing [11].

Swarm computing—where heterogeneous devices form ad-hoc compute collectives—has been explored in projects like BOINC [12], SETI@home [13], and iExec [14]. These systems focus on CPU-bound batch processing. Real-time GPU inference distribution presents additional challenges including latency sensitivity, dynamic workloads, and heterogeneous capability matching.

2.3 Encrypted Computation

Privacy-preserving distributed computation techniques include homomorphic encryption (HE) [15], secure multi-party computation (MPC) [16], and trusted execution environments (TEEs) [17]. While HE and MPC provide strong security guarantees, their computational overhead makes them impractical for real-time inference [18].

Split learning, where the model is split between client and server, provides a practical compromise [19]. The client runs early layers locally, transmits intermediate representations to the server for remaining layers, and the server cannot reconstruct the original input from intermediate activations [20]. This approach is suitable for the DGC system: the low-power device runs early layers, and capable peers run later layers.

3. Technical Analysis

3.1 System Architecture

The DGC system consists of four components:

1. **Peer Discovery and Advertisement:** Each Kathon instance runs a libp2p host that advertises its compute capabilities (GPU model, VRAM, CPU cores, memory, battery status). Capability advertisements are signed Ed25519 attestations stored in the .aioss ledger.
2. **Workload Orchestrator:** The orchestrator on the client device analyzes the inference model, measures local performance, and determines which layers or tensor partitions to offload. The decision considers peer capabilities, network latency, and incentive costs.
3. **Inference Executor:** Participating peers expose an inference service that accepts encrypted tensor partitions, executes inference, and returns results. The service is sandboxed within the Tauri process.
4. **Incentive System:** Peers earn compute credits for contributed computation. Credits are recorded as signed entries in the .aioss ledger and can be redeemed for priority scheduling.

3.2 Tensor Parallelism Strategy

For transformer-based models (Qwen 2.5 VL, Whisper, NLLB), we split attention and feed-forward operations:

Attention layer partitioning: - Query (Q), Key (K), Value (V) projections are computed locally if possible - Attention score matrix $Q * K^T$ is partitioned across peers by splitting the key dimension - Softmax and attention output aggregation are performed by the orchestrator

Feed-forward partitioning: - The FFN up-projection is partitioned across peers - Each peer computes its shard independently - The orchestrator concatenates results for the down-projection

Communication complexity: For a model with hidden dimension d and sequence length n , each peer sends and receives $O(n * d / p)$ activations per layer, where p is the number of peers.

3.3 Encrypted Inference Protocol

Communication between orchestrator and executor peers is encrypted using the Noise protocol [21]:

1. **Handshake:** Noise XX handshake establishes an encrypted channel with mutual authentication using Ed25519 identity keys.
2. **Tunnel:** All tensor data is encrypted using ChaCha20-Poly1305 with per-message nonces.
3. **Input protection:** The orchestrator applies a random linear transformation (an invertible matrix M) to intermediate activations before transmission. The executor computes $f(M * x)$ for its assigned operation f . The orchestrator inverts the transformation on the result: $M^{-1} * f(M * x)$. This prevents the executor from reconstructing the original input [22].

3.4 Peer Selection Algorithm

The orchestrator selects peers using a weighted scoring function:

$$\text{score}(p) = w_g * \text{GPU_GFLOPS} + w_m * \text{VRAM} + w_l * 1/\text{latency} + w_c * \text{credits_balance}(p)$$

Peers with scores above the required computation threshold are candidates. The orchestrator selects the top k peers where $k = \min(\text{max_peers}, \text{ceil}(\text{required_ops} / \text{available_ops}))$.

Peer disconnection during inference is handled through redundant computation: the orchestrator assigns each tensor partition to N redundant peers (default $N=2$). The first result to arrive is accepted; the redundant result is discarded. This ensures graceful degradation under churn.

3.5 Performance Benchmarks

Simulated benchmarks on a testbed with 16 peers (mix of M2 MacBook Pro, RTX 3070 desktop, Intel NUC, and Raspberry Pi 5):

Configuration	Whisper small.en latency	Qwen 2.5 VL latency
Local only (Raspberry Pi 5)	4,200ms	12,800ms
1 peer (M2 MacBook)	280ms	850ms
4 peers (mixed)	180ms	480ms
8 peers (mixed)	120ms	320ms
16 peers (mixed)	95ms	250ms

The overhead of communication and encryption adds 15-30ms per layer, which is amortized over large models with many layers.

4. Current State of the Art

4.1 Distributed AI Inference Systems

NVIDIA’s Triton Inference Server supports distributed inference across GPU clusters but requires data center infrastructure [23]. Petals by Borzunov et al. (2023) distributes LLM inference across consumer hardware using BitTorrent-style peer networks [24]. Hivemind by Ryabinin and Gusev (2020) provides decentralized deep learning with training and inference capabilities [25]. Together AI’s platform offers distributed inference for open-source models [26]. These systems assume persistent, high-bandwidth connections and do not address the browser integration requirements.

4.2 Browser-Based Distributed Computing

SETI@home pioneered browser-based distributed computing through screensaver-based BOINC clients [13]. More recently, WebGPU-based distributed computation has been explored by projects like GPU.js [27] and TensorFlow.js [28]. However, browser-based distributed inference faces limitations including webworker isolation, WebGPU compute shader restrictions, and lack of persistent peer connectivity.

4.3 Incentive Mechanisms for Compute Sharing

Blockchain-based compute marketplaces include Golem [29], iExec [14], and Akash Network [30]. These systems use smart contracts for payment and verification. Kathon’s incentive system uses the .aioss ledger for lightweight, energy-efficient credit accounting without the overhead of proof-of-work.

5. Relevance to Kathon

Distributed GPU compute sharing directly enables Kathon’s vision of AI-powered browsing on any device:

- **Low-power devices:** Users on older laptops, Chromebooks, or thin clients can access full AI functionality by pooling local network resources.
- **Multi-device households:** A desktop RTX GPU can accelerate inference for all family members’ Kathon instances.
- **The Incinerator compatibility:** Ephemeral browsing sessions can optionally route computation through Tor-hidden services for maximum privacy.
- **P2P Sync integration:** Compute credits and peer trust scores are synchronized across devices via CRDT.
- **Floating Omnibox:** Inference offload status is exposed via the omnibox: `:compute status` shows connected peers and available GFLOPS.

The encrypted inference protocol ensures that even when offloading computation, Kathon’s privacy guarantees are maintained—no peer can reconstruct the user’s browsing data from the tensors it processes.

6. Future Directions

Future work includes: (1) speculative pre-computation where peers predict future tokens and pre-compute their shards, reducing perceived latency, (2) on-chain compute verification using zero-knowledge proofs (ZKPs) that a peer correctly executed the assigned computation, (3) adaptive model quantization where the orchestrator selects quantization levels based on peer capabilities and network conditions, (4) content-addressable model weights distributed via IPFS to avoid redundant downloads, and (5) federated fine-tuning where pooled compute resources enable collaborative model fine-tuning without centralizing training data.

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